

## DOCUMENT RESUME

ED 386 982

HE 028 563

AUTHOR                   Noble, Julie; Sawyer, Richard  
 TITLE                   Alternative Methods for Validating Admissions and  
                          Course Placement Criteria. AIR 1995 Annual Forum  
                          Paper.  
 PUB DATE               May 95  
 NOTE                   28p.; Paper presented at the Annual Forum of the  
                          Association for Institutional Research (35th, Boston,  
                          MA, May 28-31, 1995).  
 PUB TYPE               Viewpoints (Opinion/Position Papers, Essays, etc.)  
                          (120) -- Speeches/Conference Papers (150)  
 EDRS PRICE           MF01/PC02 Plus Postage.  
 DESCRIPTORS           \*Admission Criteria; College Admission; \*Correlation;  
                          Courses; Decision Making; Evaluation Methods; Higher  
                          Education; \*Institutional Research; Regression  
                          (Statistics); Statistical Analysis; \*Student  
                          Placement; \*Validity  
 IDENTIFIERS           \*AIR Forum; \*Logistic Regression

## ABSTRACT

Correlational methods are compared to an alternative method based on decision theory and logistic regression for providing validity evidence for college admissions and course placement criteria. The advantages and limitations of both methods are examined. The correlation coefficient measures the strength of the linear statistical relationship between one or more measures (e.g., test score or high school grade point average) and college grade point average (GPA). However, correlations are difficult to interpret and provide little direct information about the practical implications of using particular measures and corresponding cutoff scores. They are also hampered by restrictive statistical assumptions and restriction of range problems. For example, course grades or college GPA carry values understood to range from A to F; however, experience with over 80 institutions shows that students seldom receive grades lower than a C. In addition, correlational methods are relevant only for students who are admitted to the institution or to the course, but are not readily applicable to students for whom admissions or placement decisions are yet to be made. Validity indices provide direct evidence of a measure's utility for making admissions or course placement decisions. The practical implications of using specific cutoff scores for all students of interest are shown. Validity indices are less affected than correlation coefficients by restriction of range problems in the measure(s) used to make admissions or placement decisions. This method can effectively use multiple measures for estimating students' chances of success, where success can be defined by a meaningful local standard. The data is presented in several figures and tables. (Contains 12 references.) (SW)

\*\*\*\*\*  
 \* Reproductions supplied by EDRS are the best that can be made \*  
 \* from the original document. \*  
 \*\*\*\*\*

### **Abstract**

Admissions and placement criteria are typically validated through correlation coefficients. Correlations are hard to interpret in practical terms, and are subject to a number of statistical artifacts. This paper compares correlational methods and an alternative method based on decision theory and logistic regression for providing validity evidence for admissions and course placement criteria. It emphasizes the advantages and limitations of both methods. Actual examples of admissions and placement validity evidence are provided.

### **Alternative Methods for Validating Admissions and Course Placement Criteria**

Julie Noble and Richard Sawyer

American College Testing  
Measurement and Statistical Research  
Research Division  
2201 North Dodge Street  
Iowa City, IA 52243  
319/337-1442

A paper presented at the Annual Forum  
of the Association for Institutional Research in Boston

May 30, 1995

ES 386 982

2

PRIMUS 95-1014  
MATERIAL HAS BEEN GRADED

AIR

TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)  
INFORMATION CENTER (ERIC)

1. MATERIAL OF DOCUMENT  
EDUCATIONAL RESOURCES INFORMATION  
CENTER (ERIC)  
2. The document has been reproduced as  
received from the person or organization  
or agency listed.  
3. No changes have been made to  
improve readability or quality.

- Part or all of the document is dated and the  
date of reproduction is not present
- Document does not reflect any represent

**BEST COPY AVAILABLE** 3



*for Management Research, Policy Analysis, and Planning*

**This paper was presented at the Thirty-Fifth Annual Forum of the Association for Institutional Research held at the Boston Sheraton Hotel & Towers, Boston, Massachusetts, May 28-31, 1995. This paper was reviewed by the AIR Forum Publications Committee and was judged to be of high quality and of interest to others concerned with the research of higher education. It has therefore been selected to be included in the ERIC Collection of Forum Papers.**

**Jean Endo  
Editor  
AIR Forum Publications**

### **Alternative Methods for Validating Admissions and Course Placement Criteria**

Few issues are more crucial to colleges than admissions and course placement decisions and their impact on the academic success of students. The criticality of admissions decisions is reflected in the percentages of institutions that require some standard of academic achievement for students to be admitted into college. In 1985, 84% of four-year public institutions, 89% of four-year private, and 10% of two-year public institutions required such a standard (Breland, Wilder, & Robertson, 1986). The importance of course placement decisions is reflected in the percentages of institutions offering remedial instruction: By 1993-94, 90% of all four-year college and 93% of all two-year colleges offered remedial instruction and tutoring ("Colleges and Universities Offering Remedial Instruction," 1994). Moreover, of all institutions with remedial placement programs, 90% used placement tests (locally-developed or nationally standardized) to identify students who were underprepared for standard-level courses.

One major component of admissions and placement processes involves providing validity evidence for using particular measures (e.g., locally-developed or standardized tests, high school grades, etc.) for admitting students or for placing students into particular courses. Given the "high-stakes" nature of admissions and placement decisions, colleges need to justify their admissions and placement measures and the criteria (i.e., cutoffs) used to admit or place students. Such justification is typically provided through validity studies.

In admissions, students are admitted or denied admission on the basis of their performance on specific measures (e.g., test scores, high school GPA, high school rank, etc.). These measures are typically selected and validated through correlations with college GPAs, basic descriptive information about the entering freshman class, and political considerations. Correlational statistics provide information about the statistical association between the measures and college performance. The criteria (i.e., cutoffs) for admissions are usually selected (implicitly

or explicitly) on the basis of institutional considerations and/or judgement based on student profiles and descriptive information.

At most postsecondary institutions, the placement decision is whether a student should be placed in a standard-level course, in which most freshmen enroll, or a lower-level course for students who are not academically prepared for the standard-level course. A placement decision could also be made to place a student in an advanced-level course vs. a standard course, or in a developmental course vs. a remedial course.

The measures used for making course placement decisions (e.g., locally-developed or standardized test scores, high school course work, high school grades) are typically validated through content reviews, correlations with college course grades, and institutional considerations such as class size and the number of course sections that can be offered. As is the case in admissions, setting or adjusting course placement cutoffs is usually done on the basis of faculty judgement, student profiles, and institutional considerations.

In validating measures for admissions or placement, supportive evidence should address several questions:

1. Is there a sufficiently strong relationship between the measures used and success in college/in specific courses (i.e., content fit)?
2. What minimum criteria (i.e., cutoffs) are appropriate and how do they impact student success? Institutional considerations?
3. What are the costs and benefits of adding or deleting measures used for making admissions and/or placement decisions?

This paper compares correlational methods and an alternative method based on decision theory and logistic regression for providing validity evidence for admissions and course placement criteria. Examples of admissions and placement validity studies are provided. For the purposes

of brevity and clarity, the discussion below focuses on validating admissions criteria; however, the methodology applies both to college admissions and to course placement.

#### Traditional Methods for Validating Admissions Criteria

##### Correlation Coefficients

The correlation coefficient (simple or multiple) is probably the most frequently used statistic for validating the use of measures for college admissions. In the context of college admissions, it measures the strength of the linear statistical relationship between one or more measures (e.g., test score or high school GPA) and college GPA. To the extent that the usefulness of admissions measures depend on the existence of a statistical relationship, correlational evidence is also relevant.

Correlational evidence has severe limitations, however, for validating admissions criteria. First, correlations are difficult to interpret. If a measure is already being used to admit students, the range of scores on the admissions measure is usually restricted to only those students who were admitted, i.e., only those scoring above the cutoff. Scores below the cutoff are not available. Thus, the correlations between the measure and college GPA will be artificially low due to restriction of range in the admissions measure; the correlations will be lower than those that would be obtained if all potential students were admitted. Further, as the accuracy of admissions decisions increases, the more likely admitted students are to be successful, thereby restricting the range in the college performance measure (e.g., GPA). Thus, as the accuracy of admissions decisions increases, the correlation will decrease. A low correlation could be interpreted as evidence of invalidity when it could, in fact, be evidence of the exact opposite.

In addition, correlations provide no information about the students who were not admitted and what might have happened if they had been admitted into the institution. Incomplete information is used; the total group for whom the admissions decision is actually made (referred

to here as the reference group) is not considered. (In the context of admissions, the reference group may be thought to as the applicant pool.) Using correlations as the basis of comparing potential admissions measures can therefore be misleading, as the admitted group of students may differ substantially from the reference group. (A correlation coefficient can be extended to the reference group, but only with restrictive statistical assumptions.)

Second, in most cases the measures used to describe successful college performance are either specific course grades or college GPA, with values understood to range from A to F. However, course grades and GPA do not range from A to F; experience with over 80 institutions has shown us that students seldom receive grades lower than a C. This is more frequently the case in the humanities than in mathematics or the sciences. Thus, the restriction of range problem also applies to the outcome measure.

Third, correlations involve several statistical assumptions that may not be warranted. For example, statistical inferences made from correlational and linear regression results assume that the conditional distribution of GPAs is normal. They also assume that conditional variances are equal and that the strength of the relationship between admissions measures and college performance is linear. One or more of these assumptions is usually violated, particularly the assumption of normality.

Fourth, correlations do not provide information for evaluating (either setting or adjusting) specific criteria (cutoffs) for admitting students; i.e., they cannot be used to address Questions 2 or 3. They represent the average accuracy of prediction across all values of the measures used for admissions. In a typical admissions system, however, specific cutoff values or ranges are often used. Statistics are needed to show how well a cutoff is working, relative to other possible cutoffs, so the best cutoff score can be chosen. Correlations can be used to develop

statistics to identify and validate specific cutoff values, but only under restrictive statistical assumptions and with extensive computer programming.

Fifth, correlations do not take into account the costs of incorrect admissions decisions. There are certain financial costs incurred by both the institution and by students whenever students who are not adequately prepared are admitted to college.

#### Experience/Expectancy Tables

Experience or expectancy tables provide tabular or graphical illustrations of the relationship between scores on an admission measure and college performance. Such tables can help institutions review the effectiveness of current measures and related cutoffs. However, these tables are limited to evaluating one set of admissions measures at a time. Tables using multiple measures would be so complicated as to be virtually uninterpretable. They are also limited by many of the constraints found with correlations (e.g., range restriction, statistical assumptions).

#### Admissions Validity Statistics

Statistical decision theory has been proposed by several writers, including Cronbach and Gleser (1965) and Petersen and Novick, 1976, as a useful way to analyze educational selection problems. Sawyer (1989) extended this approach to course placement systems. Sawyer's method frames validity evidence in terms of probable outcomes, given the admissions measures and criteria used. In particular, this method is intended to help identify students who have a small chance of being successful in college. Validity indices are generated from logistic regression and frequency distributions of scores on the admission measure(s) to determine the effectiveness of the admissions criteria.

The advantages of this approach, compared to traditional methods, are that it lets the strength of the relationship between admissions measure and GPA vary by scores of the admissions measure. In other words, it allows for curvilinear relationships. It also does not

require strong distributional assumptions (Houston, 1993). Further, it allows the predicting of a student's probability of success in college: A cutoff score is typically tied (either implicitly or explicitly) to a student's probability of success, which serves as the basis for this method.

Students scoring above the cutoff are admitted into college with the understanding that they have exceeded some expected probability of success. Moreover, the results pertain to the students for whom the admissions decisions are to be made (the reference group), and not only to those who are admitted.

The validity indices emphasize specific cutoff values on the admissions measure and on outcomes (i.e., GPA). For example, the indices address whether or not students with a given test score would be successful in college (e.g., GPA of 2.0 or higher). When the outcome measure is considered as a dichotomy (pass/fail), rather than as a continuous variable, the focus is placed on addressing the appropriate question, that being whether a student will be successful or unsuccessful, and less so whether a student will receive an A average vs. a B average. It also reduces the problem of restriction of range in grades/GPAs.

#### Probability of Success.

To find a student's probability of success, the statistical relationship between a student's college outcome(s) (e.g., GPA of 2.5 or higher) and his or her standing on the admissions measure is estimated using logistic regression. Logistic regression is based on a non-linear model (Hosmer & Lemeshow, 1989), resulting a student's estimated probability of success:

$$P[\text{success} | x] = \frac{1}{1 + e^{-(a + bx)}} \quad (1)$$

where  $a$  and  $b$  are regression coefficients estimated on the data,

$x$  is the score on the admissions measure,

$K$  is the cutoff score on the admissions measure, and

$e$  is the base of the natural logarithms, approximately 2.718.

This relationship is estimated from the data of students who were actually admitted and completed the term of interest. For every value of the measure, a corresponding probability of success is estimated.

The outcome measure used is a 0/1 (unsuccessful/successful) criterion variable. The criterion variable can be defined as needed to represent a meaningful outcome (e.g., GPA of C or higher (2.0 or higher)). Moreover, withdrawals (W's) can be considered as unsuccessful outcomes. With this approach, W's can be interpreted as unsuccessful outcomes without inappropriately converting them to F grades.

#### Accuracy of Admissions Decisions.

If all students in the reference group were admitted into college without using admissions criteria, we could compare predicted vs. actual outcomes. Students would be predicted to succeed or predicted not to succeed, depending on whether or not their performance on the admissions measure was above or below a hypothetical cutoff, K. Students' actual outcomes would be classified as successful or unsuccessful, for example, depending on their freshman GPAs, as shown below:

| Event | Admissions measure | Hypothetical admissions status | Eventual freshman performance |              |
|-------|--------------------|--------------------------------|-------------------------------|--------------|
|       |                    |                                | Admitted                      | Successful   |
| 1     | $\geq K$           | Admitted                       | Unsuccessful                  | Successful   |
| 2     | $\geq K$           | Admitted                       | Successful                    | Unsuccessful |
| 3     | $< K$              | Not admitted                   | Successful                    | Unsuccessful |
| 4     | $< K$              | Not admitted                   | Unsuccessful                  | Successful   |

Four percentages could be obtained from these four events:

- Event 1. The percentage of students who scored at or above the cutoff and were successful (true positive).
- Event 2. The percentage of students who scored at or above the cutoff and were unsuccessful (false positive).
- Event 3. The percentage of students who scored below the cutoff but were successful (false negative).
- Event 4. the percentage of students who scored below the cutoff and were unsuccessful (true negative).

For example, the percentage of students associated with Event 1 can be estimated by:

$$\hat{P}_1(K) = \left[ \sum_{x \leq K} P(x) \cdot n(x) / N \right] \cdot 100 \quad (2)$$

where  $\hat{P}(x)$  = estimated  $P$  [success |  $K = x$ ],

$K$  = the minimum score required for admissions (cutoff score),

$n(x)$  = the number of students whose score is equal to  $x$ , and

$N$  =  $\sum n(x)$ , the total number of students.

The percentages for Events 2, 3, and 4 can be similarly estimated.

Then, using these four percentages, three validity indices can be calculated:

1. Accuracy rate. The percentages of students in the reference group who were predicted to succeed and who did succeed (true positives) plus the percentage of reference group students who were predicted to not succeed and did not (true negatives) reflects the overall accuracy of admissions decisions, had they been made using the cutoff score, K. This sum is called the accuracy rate.
2. Success rate. The ratio of true positives to the sum of true positives and false positives shows the percentage of reference group students who would be successful, of those who were admitted using cutoff score, K. This ratio is called the success rate.

3. Percentage not admitted. The sum of the percentages of false negatives and true negatives shows the percentage of reference group students who would not be admitted using cutoff score, K. This sum is called the percentage not admitted.

Alternative cutoff scores can be examined by calculating the cell percentages for various values of K.

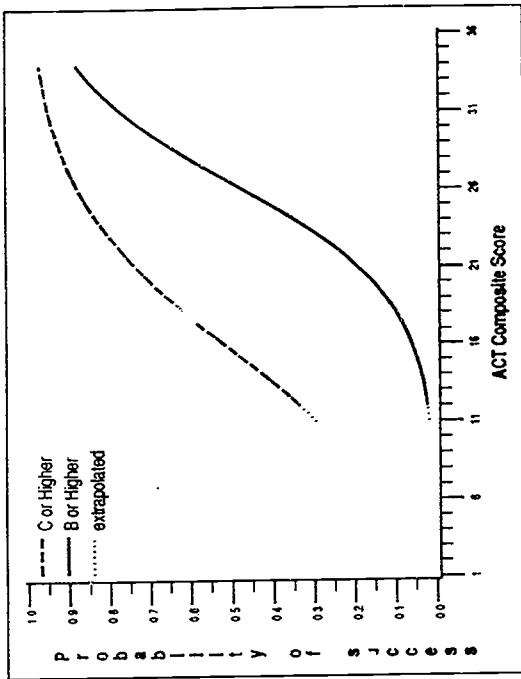
**Estimation for all reference group students.** At institutions with existing admissions criteria, it is not possible to admit all students. Probabilities of success can only be estimated indirectly, using the data of students who were admitted. Logistic regression can be used to estimate the relationship between the admissions measure and the probability of a successful outcome. The regression weights ( $a$  and  $b$  from Equation (1)) can then be used to predict a nonadmitted student's probability of success. If his/her performance on the admissions measure is known. In other words, you can estimate the probability of success for all reference group students who would be successful, regardless of their admissions status. In Figure 1 below, estimated probabilities of success are based on ACT Composite score and college success, where success is defined as a freshman GPA of B or higher or C or higher. The dashed lines illustrate where the probability of a successful outcome was extrapolated for non-admitted students.

Estimated probabilities of success, and the distributions of reference group students' values on the admissions measure, are used to calculate estimated accuracy rates, success rates, and percentages not admitted.

**Validity Indices**

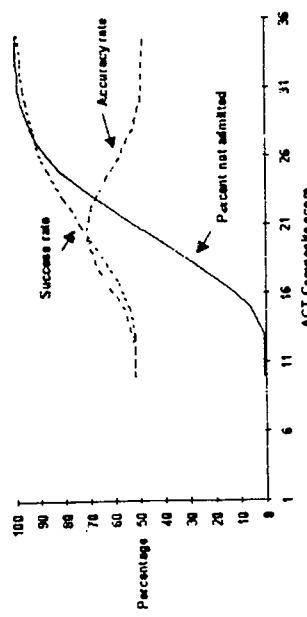
The three validity indices and the probability of success estimate what would happen if a specific cutoff on a particular set of measures were applied to a particular reference group. Thus, they address Questions 1, 2, and 3 posed at the beginning of this paper. If an admissions measure is effective, the estimated probability of success should increase as the score on the admissions measure increases, as shown in Figure 1. Further, the estimated percentage not

Figure 1. Estimated Probability of Success  
B or High and C or Higher GPA



admitted and the estimated success rate should increase as scores on the admissions measure increase, as shown in Figure 2. The estimated accuracy rate also increases as scores on the admissions measure increase, but will achieve a maximum value near a probability of success of .50. The optimal cutoff score is the score corresponding to a .50 probability of success and the maximum accuracy rate; this cutoff maximizes the percentage of correct admissions decisions. However, validity indices can be estimated for any possible hypothetical cutoff on the measure of interest.

**Figure 2. Example of Validity Indices**



**Figure 3. Validity Indices for Freshman GPA Criterion of success = B or Higher GPA**

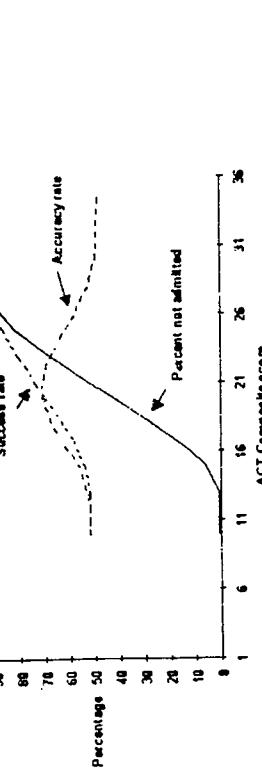
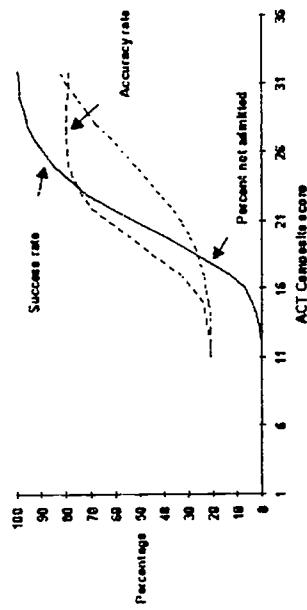


Figure 3 and Table 1 show the validity indices for the probabilities shown in Figure 1. For this institution, the success rate and percentage not admitted increase as ACT scores increase. The maximum accuracy rate of 80% corresponds to optimal cutoff scores of 27 through 30 for the B or higher GPA success criterion. The cutoff score closest to a probability of a B or high GPA is 27. The maximum accuracy rate for the C or higher GPA success criterion is 71%, which corresponds to an optimal cutoff score of 16. Using these cutoff scores, an estimated 93% (B or higher) and 7% (C or higher) of the reference group would not be admitted and, of those admitted, 62% and 72%, respectively, would be expected to be successful.

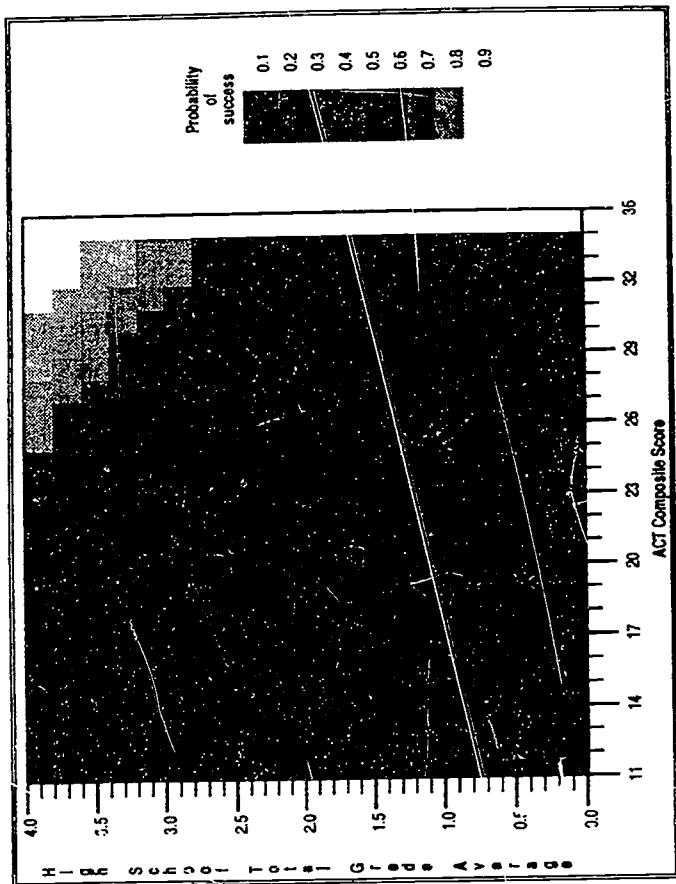
**Table 1. Validity Indices for Admissions Based on ACT Composite Score.**

| ACT<br>Composite<br>Score | Percent not<br>admitted | B or higher |            | C or higher |            | Est.<br>SR | Est.<br>AR | Est.<br>SR | Est.<br>AR |
|---------------------------|-------------------------|-------------|------------|-------------|------------|------------|------------|------------|------------|
|                           |                         | Est.<br>AR  | Est.<br>SR | Est.<br>SR  | Est.<br>AR |            |            |            |            |
| 34                        | 100                     | 79          | 88         | 30          | 97         |            |            |            |            |
| 32                        | 100                     | 79          | 83         | 31          | 96         |            |            |            |            |
| 31                        | 99                      | 79          | 80         | 31          | 95         |            |            |            |            |
| 30                        | 98                      | 80          | 76         | 32          | 95         |            |            |            |            |
| 29                        | 97                      | 80          | 72         | 33          | 94         |            |            |            |            |
| 28                        | 96                      | 80          | 68         | 34          | 93         |            |            |            |            |
| 27                        | 83                      | 80          | 62         | 36          | 92         |            |            |            |            |
| 26                        | 85                      | 79          | 52         | 41          | 89         |            |            |            |            |
| 24                        | 79                      | 77          | 47         | 45          | 87         |            |            |            |            |
| 23                        | 72                      | 74          | 42         | 50          | 85         |            |            |            |            |
| 22                        | 83                      | 70          | 37         | 55          | 83         |            |            |            |            |
| 21                        | 52                      | 63          | 33         | 60          | 81         |            |            |            |            |
| 20                        | 41                      | 55          | 39         | 64          | 79         |            |            |            |            |
| 19                        | 31                      | 48          | 27         | 67          | 77         |            |            |            |            |
| 17                        | 13                      | 33          | 24         | 71          | 73         |            |            |            |            |
| 16                        | 7                       | 28          | 23         | 71          | 72         |            |            |            |            |
| 15                        | 4                       | 24          | 22         | 71          | 71         |            |            |            |            |
| 14                        | 2                       | 23          | 21         | 70          | 70         |            |            |            |            |
| 13                        | 1                       | 22          | 21         | 70          | 70         |            |            |            |            |
| 12                        | 0                       | 21          | 21         | 70          | 70         |            |            |            |            |
| 11                        | 0                       | 21          | 21         | 70          | 70         |            |            |            |            |

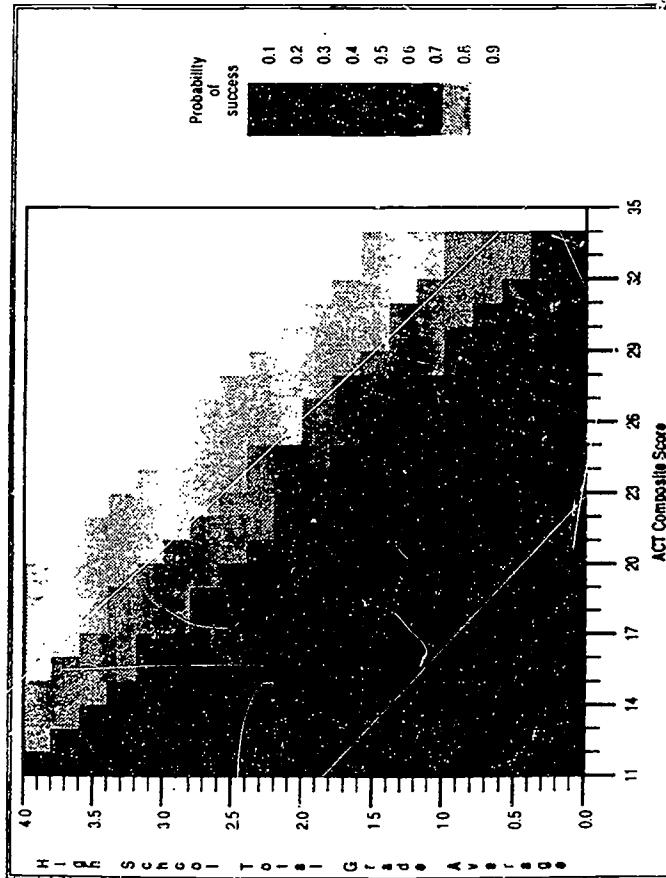
**Using Two Admissions Measures.** This methodology also accommodates multiple admissions measures. The logistic regression model includes separate regression weights for each measure ( $b_1$  and  $b_2$ ). The resulting probabilities of success and the reference group distributions of scores on both measures, as in the single measure case, are used to calculate the validity indices.

The primary difference in the two-measure case is that different values of the measures may achieve the same probability of success. Figures 4a (B or higher) and 4b (C or higher) illustrates the probabilities of success that result from using ACT Composite scores and high school averages jointly for admissions.

**Figure 4a. Probabilities of Success Based on ACT Composite Score and High School Average Criterion of Success = B or Higher GPA**



**Figure 4b. Probabilities of Success Based on ACT Composite Score and High School Average Criterion of Success = C or Higher GPA**



some minimum cutoff on either or both admissions measures must be met in order to be admitted.

Table 2 shows the validity indices corresponding to the probabilities of success shown in Figures 4a and 4b. The validity indices are anchored to probability of success values, rather than actual scores on the admissions measures, since different scores on the measures can achieve the same probability of success. As a result, the percentage not admitted differs depending on the criterion of success used.

**Table 2  
Validity Indices for College GPA Based on ACT Composite Score and High School Average**

| Probability of success for GPA based on ACT Composite Score & HS Grade Avg | B or higher          |         |         | C or higher          |         |         |
|--|----------------------|---------|---------|----------------------|---------|---------|
|  | Percent not admitted | Est. SR | Est. AR | Percent not admitted | Est. AR | Est. SR |
| .95 - .98  | 100                  | 79      | 100     | 98                   | 33      | 96      |
| .90 - .94  | 100                  | 79      | 91      | 89                   | 40      | 93      |
| .85 - .89  | 99                   | 80      | 88      | 79                   | 48      | 90      |
| .80 - .84  | 98                   | 80      | 84      | 70                   | 54      | 88      |
| .75 - .79  | 98                   | 81      | 82      | 58                   | 60      | 85      |
| .70 - .74  | 97                   | 81      | 79      | 45                   | 66      | 82      |
| .65 - .69  | 95                   | 82      | 76      | 38                   | 69      | 81      |
| .60 - .64  | 94                   | 82      | 73      | 29                   | 71      | 78      |
| .55 - .59  | 90                   | 83      | 67      | 25                   | 72      | 77      |
| .50 - .54  | 88                   | 83      | 65      | 16                   | 72      | 75      |
| .45 - .49  | 86                   | 83      | 62      | 12                   | 72      | 73      |
| .40 - .44  | 84                   | 82      | 59      | 5                    | 71      | 71      |
| .35 - .39  | 82                   | 82      | 57      | 3                    | 70      | 70      |
| .30 - .34  | 78                   | 81      | 53      | 1                    | 70      | 70      |
| .25 - .29  | 70                   | 77      | 46      | 1                    | 68      | 69      |
| .20 - .24  | 64                   | 74      | 42      | 0                    | 69      | 69      |
| .15 - .18  | 51                   | 65      | 36      | 0                    | 69      | 69      |
| .10 - .14  | 38                   | 56      | 31      | 0                    | 69      | 69      |
| .05 - .09  | 20                   | 40      | 25      | 0                    | 69      | 69      |
| .01 - .04  | 1                    | 22      | 21      | 0                    | 69      | 69      |

As Figure 4b shows, ACT Composite scores of 11 to 32 and high school averages of 0.0 to 4.0 achieve a probability of a C or higher GPA of .50. The steepness of the contour plot illustrates the relative contribution of each measure to the logistic regression model. Using these results decision-makers can either choose a compensatory approach to admissions (e.g., student with higher ACT Composite scores can have lower high school averages, and students with lower ACT Composite scores need to have higher high school GPAs), or a conjunctive approach where

Using ACT Composite and high school averages jointly would achieve an estimated maximum percentage of correct admissions decisions of 83% (B or higher) and 72% (C or higher). Using the B or higher cutoffs, 88% of the reference group would not be admitted; the corresponding percentage for the C or higher success criterion was 16%. Of those admitted students, an estimated 65% (B or higher) and 75% (C or higher) would be successful.

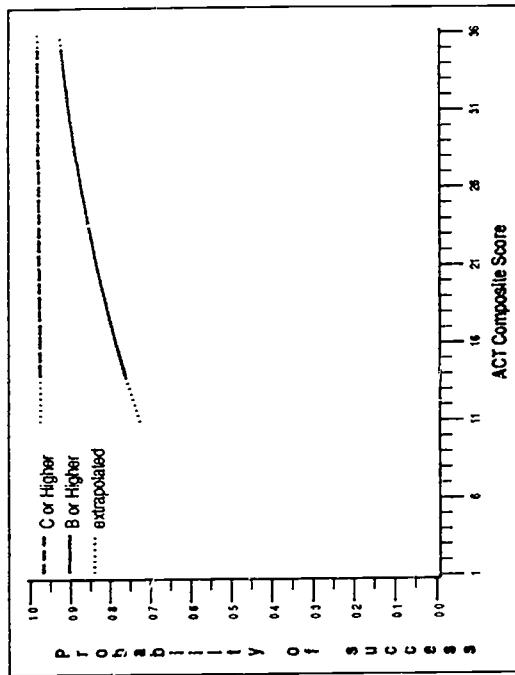
By comparing maximum accuracy rates for one and two-predictor models, decision-makers can determine the utility of the second predictor. In the above example, the maximum accuracy rate for the B or higher success criterion was 80% based on the ACT Composite score, and 83% for the combination of ACT Composite score and high school GPA. This increase is quite small relative to the added complexity of a second predictor variable. (Note: the corresponding simple and multiple  $R^2$ s are .37 and .50). This situation is of particular concern in course placement, where adding a local placement test as a second placement variable might or might not be cost effective, depending on the increase in correct placement decisions yielded by adding a second test.

**Computer software issues.** Logistic regression analyses can be run in either SAS or SPSS; subsequent data manipulation to develop estimated probabilities of success and validity indices for the reference group can also be done using these software packages. I recommend SAS mainly because of its file handling capabilities; SAS Version 6 includes a PROC LOGISTIC procedure that works well. SPSS also has a LOGISTIC REGRESSION procedure, and the manual provides a very accessible discussion of the statistics. The one limitation to the SPSS version appears to be that SPSS does not output the parameter estimates to a system file. This is not a problem if the researcher is willing to hard-code them into subsequent programs.

**Limitations.** The validity indices generated using this approach can be influenced by range restriction in course outcomes. For example, if very few or no students are unsuccessful

(e.g., below a GPA of 2.5) or, for course placement, the course is either very easy or very hard, it is difficult to estimate probabilities of success, and thus the validity indices. Figure 5 below illustrates a situation where 87% of the students had GPAs of 3.0 or higher, and 98% had GPAs of 2.0 or higher.

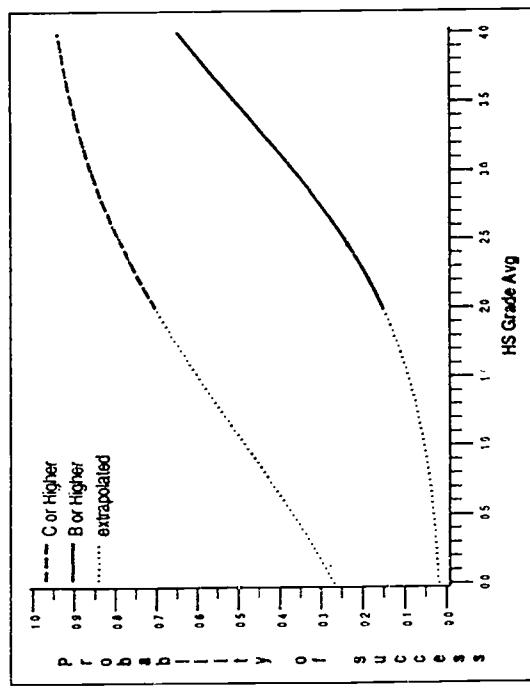
Figure 5. Impact of GPA Range Restriction on Probabilities of Success



A restricted range in the measures used for admissions (typically for highly selective institutions) can also be a problem. This problem is most likely to occur when a measure is already being used to make admissions or placement decisions. It can also occur with admissions and placement measures based on rating scales with very few levels of performance, such as grade equivalents. Figure 6 and Table 3 below illustrate such an example.

As shown in Table 3, the maximum accuracy rate for the C or higher success criterion corresponds to the lowest grade average cutoff; 85% of the reference group would be successful by just being admitted. In contrast, the maximum accuracy rate for the B or higher success criterion corresponds to the highest grade average cutoff.

**Figure 6. Impact of Range Restriction on Probabilities of Success**



Large prediction errors can also result from range restriction in the admissions measure. Schiel and Noble (1993) compared logistic regression functions estimated from truncated subsets of a data set that was not subject to prior selection. When truncation involved less than 15% of the reference group, the resulting errors were small, but large amounts of truncation (e.g., 50%) resulted in large errors. Using computer simulations, Houston (1993) examined the effects of truncation on the accuracy of estimated probabilities of success. He found increases in standard error from 6% to 43% when the reference group was truncated at the 25th, 50th, and 75th percentiles, as compared to the standard error associated with no truncation.

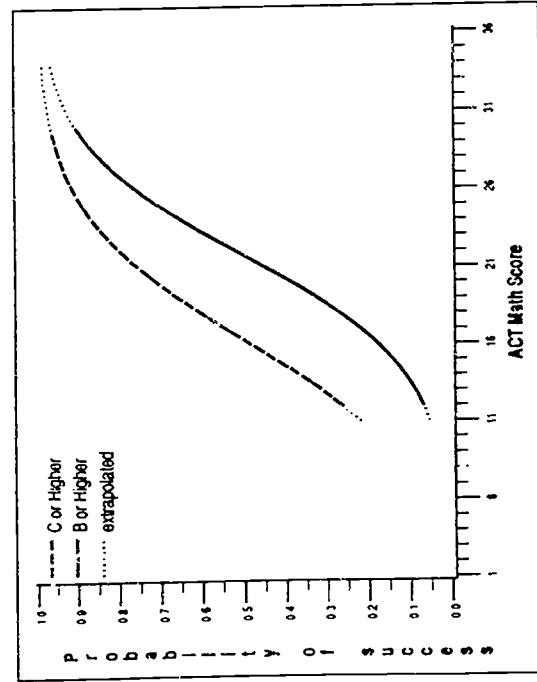
Estimated probabilities of success are also influenced by sample size. The sample sizes needed to estimate the logistic regression weights are larger than those needed for linear

regression (Houston, 1993). Houston also found that to have a standard error of 5% for estimating accuracy rates, then prior selection should involve no more than 25% of the reference group and the sample size should be at least 100.

#### A Samples From Course Placement

For course placement, the outcome variable is the grade received in a particular course (i.e., B or higher, or C or higher, grade). In this example, the course was Intermediate Algebra; the reference group consisted of 1516 students, of which 433 completed the course. The probabilities of success are shown in Figure 7.

**Figure 7. Estimated Probability of Success in Intermediate Algebra Based on ACT Mathematics Score**



As Figure 7 shows, an ACT Mathematics score of 22 is associated with a probability of a B or higher grade of approximately .50. The corresponding C or higher cutoff score is 16

(probability of success = .44). The figure also shows that reference group students scored below and above those students who enrolled in Intermediate Algebra. It is likely that reference group students could have also been placed in upper-level mathematics courses (such as college algebra or calculus), as well as lower-level courses, on the basis of ACT Mathematics score.

The validity indices for this course are shown in Table 4. For this course, the maximum accuracy rates were 66% (B or higher) and 74% (C or higher); of the students in the reference group, an estimated 66% and 74%, respectively, would be successful if the optimal cutoff score was used to place students. Using the B or higher success criterion, 56% of reference group students would be placed in a lower-level course; for the C or higher criterion, 5% would be placed in a lower-level course. Further though, the maximum increase in the accuracy rate for the C or higher success criterion was only 2%, the increase for the B or higher criterion was 22%.

**Table 4. Validity Indices for Intermediate Algebra Based on ACT Mathematics Score**

| ACT Math Score | Percent placed in lower-level course | B or higher |         | C or higher |         |
|----------------|--------------------------------------|-------------|---------|-------------|---------|
|                |                                      | Est. AR     | Est. SR | Est. AR     | Est. SR |
| 34             | 100                                  | 54          | 96      | 21          | 98      |
| 32             | 100                                  | 55          | 95      | 21          | 98      |
| 31             | 99                                   | 55          | 94      | 28          | 97      |
| 30             | 95                                   | 55          | 92      | 29          | 97      |
| 29             | 97                                   | 56          | 90      | 30          | 96      |
| 28             | 95                                   | 58          | 87      | 32          | 95      |
| 27             | 92                                   | 60          | 84      | 35          | 94      |
| 26             | 81                                   | 65          | 77      | 44          | 91      |
| 25             | 74                                   | 67          | 74      | 49          | 90      |
| 24             | 66                                   | 68          | 70      | 54          | 88      |
| 23             | 55                                   | 68          | 68      | 60          | 86      |
| 22             | 46                                   | 67          | 62      | 65          | 84      |
| 21             | 34                                   | 64          | 58      | 69          | 82      |
| 20             | 19                                   | 27          | 62      | 55          | 72      |
| 19             | 17                                   | 53          | 50      | 74          | 76      |
| 18             | 5                                    | 50          | 48      | 74          | 74      |
| 17             | 2                                    | 48          | 47      | 73          | 73      |
| 16             | 1                                    | 47          | 46      | 73          | 73      |
| 15             | 0                                    | 46          | 46      | 72          | 72      |
| 14             | 0                                    | 46          | 46      | 72          | 72      |
| 13             | 0                                    | 46          | 46      | 72          | 72      |
| 12             | 0                                    | 46          | 46      | 72          | 72      |
| 11             | 0                                    | 46          | 46      | 72          | 72      |

## Discussion

Though correlations provide evidence of the statistical linear relationship between admissions or placement measures and college performance, they provide little direct information about the practical implications of using particular measures and corresponding cutoff scores. Further, they are hampered by restrictive statistical assumptions and restriction of range problems; they are relevant only for students who are admitted to the institution or to the course, but are not readily applicable to students for whom admissions or placement decisions are to be made.

Validity indices developed using Sawyer's (1989) methodology provide direct evidence of a measure's utility for making admissions or course placement decisions. The practical implications of using specific cutoff scores for all students of interest are also shown. Though affected by restriction of range problems in the outcome variables, validity indices are less affected than correlation coefficients by restriction of range problems in the measure(s) used to make the admissions or placement decisions. Further, this method can effectively use multiple measures for estimating students' chances of success, where success can be defined by a meaningful local standard.

## References

- Breland, H., Wilder, G., & Robertson, N. (1986). Demographics, standards, and equity challenges in college admissions. AACRAO, ACT, CEEB, and NACAC.
- Cronbach, L. J. & Gleser, G. C. (1965). Psychological tests and personnel decisions. Urbana, Illinois: University of Illinois Press.
- Education Week (April 13, 1994), Volume 12, Number 29.
- Hosmer, D. W. & Lemeshow, S. (1989). Applied logistic regression. New York: John Wiley & Sons, Inc.
- Houston, W. M. (1993). Accuracy of validity indices for course placement systems. Paper presented at the annual meeting of the American Educational Research Association, Atlanta.
- Petersen, N. S. & Novick, M. R. (1976). An evaluation of some models for culture-fair selection. Journal of Educational Measurement, 13, 3-29.
- Sawyer, R. L. (1989). Validating the use of ACT Assessment scores and high school grades for remedial course placement in college. (ACT Research Report No. 89-4). Iowa City, IA: American College Testing.
- Sawyer, R. L. (1993). Decision theory models for validating course placement systems. Paper presented at the annual meeting of the American Educational Research Association, Atlanta.
- Sawyer, R. L. (1994, April). Eliciting utility functions for validating course placement systems. Paper presented at the annual meeting of the National Council on Measurement in Education, New Orleans.
- Sawyer, R. L. (1995, April). Eliciting utility functions for validating course placement systems. Paper presented at the annual meeting of the National Council on Measurement in Education, San Francisco.
- Schial, J. & Noble, J. (1992). The effects of data truncation on estimated validity indices for course placement. (ACT Research Report No. 92-3). Iowa City, IA: American College Testing.
- Schulz, E. M. & Noblu, J. (1995). Selecting optimal cutoff scores for course placement. Paper presented at the annual forum of the Association for Institutional Research, Boston.